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# Selecting coastal hotspots to storm impacts at the regional scale: a Coastal Risk Assessment Framework

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A R T I C L E I N F O

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A B S T R A C T

Managing coastal risk at the regional scale requires a prioritization of resources along the shoreline. A transparent and rigorous risk assessment should inform managers and stakeholders in their choices. This requires advances in modelling assessment (e.g., consideration of source and pathway conditions to define the probability of occurrence, nonlinear dynamics of the physical processes, better recognition of systemic impacts and non-economic losses) and open-source tools facilitating stakeholders' engagement in the process.

This paper discusses how the Coastal Risk Assessment Framework (CRAF) has been developed as part of the Resilience Increasing Strategies for Coasts Toolkit (RISC-KIT). The framework provides two levels of analysis. A coastal index approach is first recommended to narrow down the risk analysis to a reduced number of sectors which are subsequently geographically grouped into potential hotspots. For the second level of analysis an integrated modelling approach improves the regional risk assessment of the identified hotspots by increasing the spatial resolution of the hazard modelling by using innovative process-based multi-hazard models, by including generic vulnerability indicators in the impact assessment, and by calculating regional systemic impact indicators. A multi-criteria analysis of these indicators is performed to rank the hotspots and support the stakeholders in their selection.

The CRAF has been applied and validated on ten European case studies with only small deviation to areas already recognised as high risk. The flexibility of the framework is essential to adapt the assessment to the specific region characteristics. The involvement of stakeholders is crucial not only to select the hotpots and validate the results, but also to support the collection of information and the valuation of assets at risk. As such, the CRAF permits a comprehensive and systemic risk analysis of the regional coast in order to identify and to select higher risk areas. Yet efforts still need to be amplified in the data collection process, in particular for socio-economic and environmental impacts.

## 1. Introduction

Increasing coastal threats, exposure and risk pose a problem for the sustainable development and management of our coasts (Hallegatte et al., 2013; IPCC, 2015). Firstly it requires a re-evaluation of the current standard of protection of areas behind which exposure has increased. Secondly it necessitates the recognition of newly exposed and non-defended areas resulting from the expansion of built-up areas (Neumann et al., 2015). Thirdly it requires an assessment of potential indirect and systemic impacts to better measure the resilience of coastal communities (UNISDR, 2015). As such, there is an increased demand for action which consequently requires a prioritization in the choice of actions and funding to be allocated for mitigating the risk. Scarcity in resources imposes the need for a transparent and rigorous risk assessment process, including various scales of governance (Driessen et al., 2016; Alexander et al., 2017). A succession of tools and approaches have been developed to support decision-making processes with the objective of better integration of various threats and impacts, better stakeholder involvement as well as a wider application of those tools through the provision of open-source methodologies and by increasing ease of use (Zanuttigh et al., 2014; Torresan et al., 2016a; Vafeidis et al., 2008). The RISC-KIT tool-kit (van Dongeren et al., 2014) sustains this transfer of

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knowledge within the research and development, the engineering, and the coastal management community by providing a series of tools to better understand coastal risk, to measure that risk at various coastal scales and to assess the effectiveness and potential of Disaster Risk Reduction (DRR) measures.

The RISC-KIT project acknowledges that the high demand in terms of data, time and resources required for a detailed risk-assessment is prohibitive for a comprehensive and detailed risk assessment of an entire coastal region. Such an assessment requires high-resolution (e.g., 10 m scale) predictions for multiple (thousands of) scenarios using computationally-intensive high-fidelity modelling techniques, as well as detailed information on receptors, vulnerability and disaster reduction measures, and is therefore impractical for application at the regional or national (100–1000 km) scale.

Within this context, the RISC-KIT project provides a comprehensive and systematic methodology, called the Coastal Risk Assessment Framework (CRAF), in which a first assessment of impact and risk is carried out at the regional scale to identify so-called hotspots, defined as specific locations with the highest risk (on the scale of 1–10 km). A further detailed analysis of coastal hazards and impacts, as well as the effectiveness of DRR measures can subsequently be carried out at individual hotspots using the RISC-KIT hotspot tool (Bogaard et al., submitted).

This present paper presents the two-step methodological approach adopted in the framework. The overall CRAF is first introduced in section 2 outlining differences between the two phases of the approach. The large-scale coastal index (CRAF Phase 1) approach is then detailed in section 3 with explanations of the index calculation, methodological choices and of the assessment process for probability, hazards and exposure elements of the index. Section 4 focuses on the CRAF Phase 2 explaining the hazard computation, the impact assessment model and the multi-criteria analysis used to perform the hotspot selection. This contribution presents and discusses the CRAF methodology and some of the lessons learned in section 5. However, this paper also complements six other papers in this special issue, with some of them applying this methodology. In particular, the lessons learned from existing CRAF applications are further discussed in the "Storm-induced risk assessment: evaluation of tool application" paper (Ferreira et al., 2017). For a detailed discussion and validation of the CRAF application on specific case studies the reader is also directed to papers detailing its application on two Italian coasts (Emilia-Romagna coast and Liguria coast (Armaroli and Duo, 2017; De Angeli et al., 2017)), on the North Norfolk coast in England (Christie et al., 2017), on the coast of Kristianstad in Sweden (Barquet et al., 2017) and on the Catalonian coast in Spain (Jiménez et al., 2017).

## 2. Coastal risk assessment framework

Existing approaches have been developed for supporting the coastal vulnerability analysis along the coast at different scales, amongst them are: the model DIVA (Dynamic Interactive Vulnerability Assessment) (Hinkel and Klein, 2009); the RVA method (Regional Vulnerability Assessment) (Torresan et al., 2012); CERA (Coastal Erosion Risk Assessment) (Narra et al., 2017); or the CRI-LS index (Multi-scale Coastal Risk Index for Local Scale) (Satta et al., 2016). GIS index-based approaches dominate (Gornitz, 1990) and principally consist of combining different standardised indicators which are derived from various sources of information. These approaches have their advantages as they are user-friendly; do not require high level of expertise; can use various source of data and integrate uncertainty in the assessment by performing relative comparisons (Satta et al., 2016; Balica et al., 2012). It must be noted, here, that the number of indicators included in these indices has significantly increased over the years. Whereas Gornitz (1990) (Gornitz, 1990) only included hazard indicators (i.e. geomorphology, slope, sea level change, erosion, tidal range, wave height), new indices include dozens of them (Torresan et al., 2012; Narra et al., 2017; Satta et al., 2016; Balica et al., 2012). The increase in the number of indicators is explained by the needs of multi-hazard assessment (e.g. inclusion of drought, surge, and cyclone), the inclusion of socio-economic and environmental indicators (e.g. land use, population, cultural heritage) and resilience/resistance indicators (e.g. presence of shelters, defences, and awareness). The better consideration of a full impact assessment benefits the analysis. However, the combination of multiple indicators using simple additive or multiplicative operations may be questioned in particular if there is some degree of overlap between indicators (Balica et al., 2012). It also reduces the simplicity of the index and, as such, it requires a better understanding by the users of the indicators (Torresan et al., 2012). In particular, levelling everything to an "average" value may not be representative with a potentially high impact to a certain indicator being minimised by the lower values of other impacts. Such levelling may then lead to a false sense of low impact overall. A multi-hazard indicator also poses a problem of double-counting or miscounting. As such, in the case of flooding and erosion the number of buildings exposed to these hazards differs. For assets exposed to both hazards there is a question whether a building which suffers from flooding and then also collapses due to erosion should be scored higher than a building collapsing just by erosion; as the additional losses caused by the flooding become irrelevant. Another limitation of the existing approaches is the lack of assessment of indirect and systemic impacts. The vulnerability of the critical infrastructures (road network, utilities) and the consequences for the population not exposed to the hazard but dependant of these services is often not considered. Yet a comprehensive understanding and representation of the coastal system is required (Narayan et al., 2012).

An alternative existing approach is to use methods integrating processed-based morphological models, inundation models and flood loss assessment models in order to assess the impacts and the risk following the source-pathway-receptor-consequence approach (Schanze et al., 2006). Processed-based morphological and inundation models permit the generation of flood and erosion maps, which can be used as an input for flood loss assessment models. Flood loss assessment models have mainly been developed to assess fluvial flooding impacts (Meyer et al., 2013; Jongman et al., 2012; Gerl et al., 2016); e.g., HAZUS in the USA, LATIS in Belgium, HIS-SSM in Netherlands, FLEMO in Germany, the MCM in England and Wales. DESYCO and THESEUS are examples of recent GIS integrated coastal models using flood loss assessment models (Zanuttigh et al., 2014; Torresan et al., 2016b). They are deterministic models combining vulnerability functions, receptor maps and hazard maps to estimate the consequential losses. The vulnerability functions are often expressed as depth-damage curves and vary from one country to another for a better representation of the characteristics of the receptors but large uncertainty remains in these functions (Jongman et al., 2012; Penning-Rowsell et al., 2013). The resulting direct impacts can then be input into additional models, such as input-output models, computable general equilibrium models, network analysis or object-orientated models to better assess indirect and cascading impacts (Carrera et al., 2015; Demirel et al., 2015; Serre, 2016; Ouyang and Dueñas-Osorio, 2014; Eusgeld et al., 2009).

This paper recognises the advantages of using both the GIS index-based and integrated modelling approaches to support a risk assessment and the selection of hotspots in collaboration with stakeholders at the regional scale. Such arrangement permits bridging scientists and practitioners' perspectives. From a research standpoint advancement are expected in assessment modelling including; deriving the coastal hazard from the external boundary conditions by better recognizing the nonlinear dynamics of the physical processes, associating source and pathways in the probability of occurrences, improving the consideration of indirect impacts, involving stakeholders and supporting an integrated assessment. From a practical perspective it is essential to develop a tool that could be used with confidence. The inherent question in developing such a framework is the level of simplicity that could be achieved. Simplicity is necessitated as data, skills and resources are limited.

However, a lack of complexity will also lead to a non-applicable framework and may cause incorrect hotspot selection and thereby reduce user confidence in the results, and to a non-effective framework. As such, the CRAF utilises two successive levels of analysis to balance these needs: a screening approach using the coastal vulnerability index (Phase 1) and an integrated approach (Phase 2) (Table 1).

Phase 1 systematically screens the whole coast utilising sectors of 1-km average length, the objective being to identify potential hotspots. This phase eliminates low risk areas and permits the grouping of sectors with higher risk as hotspots by using hazard probability, pathway and hazard computation, consequence assessment and an indicator calculation method. This approach responds to some of the research challenges (probability of occurrence, stakeholders, integrated assessment) without requiring large resources. This screening approach is particularly appropriate when stakeholders have limited knowledge of their coastal risk and aims to optimise risk evaluation resources. The assessment consists of the calculation of exposure and hazard indicators which are combined in a coastal index for each sector and, then, in grouping these sectors in potential hotspots of 1–10 km. Phase 1 requires the users to understand the coastal processes and the geographical context and to choose and develop an appropriate approach by combining methodologies proposed in the guidance document (Viavattene et al., 2015a). The principles are further detailed in section 3.

Phase 2 provides the tools and methods to fill the gap between the simplicity of a coastal index technique and the very complex modelling processes required at an economic appraisal level. In particular a specific model (INDRA for Integrated Disruption Assessment Model) has been developed for the impact calculation (Viavattene et al., 2016). An initial step, before using INDRA, is the assessment of the hazards intensities for each hotspot. Phase 2 improves the regional risk assessment by increasing the resolution of the hazard assessment (non-uniform and 100 m or less transect approach), by using an innovative 1D multi-hazard pathway and 2D inundation modelling techniques. A coastal Vulnerability Library Indicators (Viavattene et al., 2015b) has also been developed to support users in accessing or developing generic vulnerability indicators for various types of receptor for inputting in the INDRA impact model. The INDRA model computes both direct and indirect impacts at the potential hotspots; and calculates regional systemic impact indicators (Table 1). A multi-criteria analysis can then be performed with end-users to select a final hotspot. Each component of Phase 2 is presented in section 4 of this paper.

## 3. CRAF phase 1: large-scale coastal index

### 3.1. Index calculation

The "identification of hotspots" is a screening process which distinguishes several likely high-risky locations along the coast by assessing the potential exposure for every coastal sector of approximately 1 km alongshore length. The approach calculates Coastal Indices (CI) following an existing and established approach. The Index-Based Method combines several indicators into a single index, thereby allowing a rapid comparison of coastal sectors. However, there is not one standardised approach, with the type of indicators considered, the way they are ranked and the formula used to combine variables differing between studies (Gornitz, 1990; Balica et al., 2012; McLaughlin et al., 2002; Ramieri et al., 2011). In the CRAF, a simple approach is adopted which combines five-classes ranking hazard and exposure with equal weight in a square root geometric mean following Gornitz and other approaches (Gornitz, 1990; Ramieri et al., 2011; Thieler and Hammer-Close, 1999):

$$\boldsymbol{CI} = \left(\boldsymbol{i}_{\boldsymbol{hazard}} * \boldsymbol{i}_{\boldsymbol{exposure}}\right)^{1/2} \tag{1}$$

In contrast to other developed methods (e.g., (Alexandrakis and Poulos, 2014)), where several coastal hazards contribute to a single index, this framework allows multiple hazards and multiple impacts to be addressed although the approach as the CRAF is applied individually for each hazard. In Phase 1 the assessment is limited to the exposure (including the relative importance of the assets), with a detailed vulnerability analysis only being considered in Phase 2. In other terms if we consider the risk equation as a function of probability (hazard, exposure, vulnerability), vulnerability is considered equal for all exposed elements.

Hazards and exposure are approached slightly differently in their ranking. The different types of hazard are considered separately whereas different exposures are combined for each hazard type. This was chosen because the spatial extent of the exposure is primarily dependent upon the hazard and geomorphological setting, and therefore the calculation of a single Coastal Index for all hazards might be misleading. The multiple index approach was also considered more appropriate for the coastal manager to better reflect the regional variability of the risk with regards to differences in expected responses, mitigations and management approaches for each hazard.

Hazards are ranked from 0 to 5 (none to very high) whereas exposures are scored from 1 to 5. The overall exposure is obtained by the geometric mean with equal weighting of all exposure indicators:

$$\boldsymbol{i}_{\boldsymbol{exposure}} = \left[\!\left[ \left(\boldsymbol{i}_{\boldsymbol{exp}1} * \boldsymbol{i}_{\boldsymbol{exp}2}, \ldots * \boldsymbol{i}_{\boldsymbol{expn}}\right) \right]\!\right]^{1/\boldsymbol{n}} \tag{2}$$

with 1 to n referring to the exposure variables considered in the assessment. The use of a geometric mean with $n$ variables precludes the use of a null value, and therefore the lowest value of 1 expresses none or very low exposure level. This minor difference in the ranking value between hazard and exposure indicators has no consequences on the outcomes of the index as the objective is to identify the sectors with the highest values. High values of 4 and above are obtained exclusively by the combination of high (H) and very high (VH) indicators. A CI value of 3.2 is used as a threshold limit to identify hotspots, as this value is obtained

**Table 1**
Level of analytical detail performed for CRAF Phase 1 and Phase 2.

| | CRAF Phase 1 | CRAF Phase 2 |
|---|---|---|
| | GIS index-based approach | Integrated modelling Approach |
| Assessment area | Entire regional coast (~100 km) | 3–4 potential hotspots within the regional coast boundary |
| Hazard pathway assessment model | Simple (empirical) model | 1D, process-based, multi-hazard |
| Hazard pathway assessment scale | Uniform hazard pathway per sector (~1 km) | Multiple hazard pathway computations per sector (up to 100 transects per km, given the computational constraints) |
| Hazard model (inundation extent) | Simple bathtub/overwash extent model | 2D inundation model |
| Computation of hazard probability | Response approach (in the case of absence of long time series, event approach) | Response approach (in the case of absence of long time series, event approach) |
| Receptor and vulnerability information | Exposure only (receptor types and associated ranking values) | Receptor and vulnerability data (Coastal Vulnerability Library (Viavattene et al., 2015b)), at individual or aggregated (neighbourhood) scale |
| Calculation of impact | Exposure indicators | INDRA model (Viavattene et al., 2016): Indicators of direct and indirect impacts and MCA |
| Outcomes | Coastal Index per sector – potential hotspots | Regional Score per hotspot using a Multi Criteria Analysis – Selected hotspot for detailed risk-assessment |

exclusively by the combination of medium (M) to VH indicators (3.2 is the rounded root value of low (L) and VH (2*5) and is greater than the root value of M and M (3*3)). Below such values it is rather difficult to identify and differentiate the hotspots as the combinations of very low (VL) to VH indicators make similar CI results possible.

### 3.2. Probability of occurrence of a storm induced hazard

When locations are evaluated along the coast to make decisions about risk management, it is important to have a robust criterion to undertake a comparable analysis. Using the CRAF, the selected common factor to compare hazards is their probability of occurrence (Jiménez et al., 2009; Bosom and Jiménez, 2011). Thus, a coastal hotspot is defined here as a location with a risk magnitude significantly higher than neighbouring areas for a given probability of occurrence. Since storm-induced hazards depend on more than one single variable (e.g., wave height, period, duration, water level), different combinations of water level and wave conditions (storm events) will result in hazards of similar magnitudes. Due to this, the framework uses the so-called response approach (Garrity et al., 2007), where the probability of occurrence is directly calculated for the hazard without making any assumption about the relationship between different variables controlling the magnitude of the hazards. To do this wave and water level time series are used to compute time series of the hazard of interest. An extreme distribution is subsequently fitted to the obtained hazard dataset. This so-called "response approach" has been increasingly used in vulnerability and risk assessments of storm impacts (e.g (Jiménez et al., 2009; Divoky and McDougal, 2007; Callaghan et al., 2008, 2013; Bosom and Jiménez, 2010; Corbella and Stretch, 2012).), in place of the more traditional "event approach", in which an extreme value distribution is fit to the offshore wave or water level time series. Fig. 1 shows an example of differences in the hazard magnitude (wave runup, $Ru_{2\%}$) associated with a given probability of occurrence by using both methods (response and event approach). The magnitude of the difference between the response and event approach will depend on the characteristics of the climate variables controlling the hazard as well as how they are combined to assess it. In Fig. 1, this is illustrated for an extreme regime of wave-induced runup at one point of the Catalan coast (Sánchez-Arcilla et al., 2009). Since $Ru_{2\%}$ depends on wave height and period and these are uncorrelated in this part of the Mediterranean coast, significant differences in $Ru_{2\%}$ are obtained.

### 3.3. Erosion and inundation hazard assessment using dynamic inundation models

In CRAF Phase 1, hazards are assessed along the coastal zone by using selected key indicators that are obtained from simple parametric models. This permits a quick assessment of their magnitude for a large number of

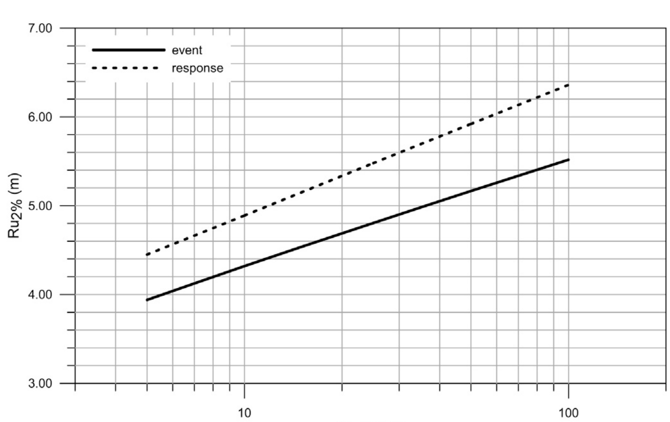


**Fig. 1.** Extreme wave runup regimes in the Catalan coast computed using the event and the response approaches (modified from Sánchez-Arcilla et al (Carrera et al., 2015).).

events (to obtain reliable probabilistic distributions by using the response approach) and for a large number of positions along the coast (to properly characterize the spatial distribution of hazards at regional scale).

Storm-induced hazards in coastal areas can be classified simply as flooding- and erosion-related hazards, since inundation, overwash and coastal erosion are the dominant processes taking place on sedimentary coastlines under the impact of coastal storms. Coastal flooding groups all hazards related to temporary inundation of the coastal zone due to storm-induced variations of the water level at the shore (overwash, overtopping, and inundation). Overtopping occurs if the total water level exceeds the height of the beach/dune or any existing protection, flooding the hinterland. The worst condition occurs when large areas connected to the sea have an elevation below the storm-induce water level (e.g. akin to a bathtub). However, this would only occur in cases where such a water level would remain in place for a time long enough to ensure that the whole hinterland can be inundated during the storm. Usually, this is the case for steep coastal sections where elevation increases monotonically (more or less) landwards over a short distance from the coast. In such cases, the bathtub approach is adopted to delineate the maximum potential inundation extension for the target total water level. However, in extensive low-lying coastal areas where the storm water level is dominated by wave-induced runup this bathtub approach is seldom realistic. Under these conditions, the extension of the potentially affected surface is characterized by the extension of overwash. This overwash extension is estimated in this phase by using simple approaches such as the one proposed by Donnely (Donnelly, 2008) or by Plomaritis et al. (2017).

The point where the storm water level intersects the beach is calculated for each profile, taking into account the corresponding water level and local beach topography. This water level is given by the combination of high water levels (storm surge, $\xi m$, plus high tides, $\xi a$) and wave action (runup, $Ru$). On open coasts/beaches, it is assumed that $\xi a$ and $\xi m$ are (or can be) extracted from measured/modelled time series, and the remaining part, $Ru$, is calculated for a given wave climate scenario. In the simplest way, its assessment is usually undertaken by applying empirical models, which will predict its magnitude as a function of wave conditions (e.g., wave height $H$ and period $T$; usually given as deep water values). There are numerous formulas to predict this, derived from laboratory and field experiments, and with different performance when compared with real data (see (Roberts et al., 2010; Mather et al., 2011; Vousdoukas et al., 2012; Matias et al., 2014)). Among these, one of the most extensively used is that proposed by Stockdon et al. (2006). However, it is recommended that any model specifically validated for local conditions or derived and used for similar characteristics be utilised. Fig. 2 shows all steps involved in the assessment of the inundation hazard in this phase of the framework for an open sandy coast.

Storm-induced erosion is assessed in CRAF Phase 1 by means of simple approaches able to efficiently work at large spatial scales and with a high number of events to obtain a probability distribution. To do this, the induced hazard is calculated with a structural function specifically derived for storm impacts on beaches, with the function to be selected depending on its performance for the site conditions (use of specific models calibrated for the site or for similar conditions). One example of this approach is the structural erosion function proposed by Mendoza and Jiménez (2006). This predicts the eroded volume in the inner part of the beach during a storm, assuming that the response is controlled by the induced cross-shore sediment transport. It is defined by a simple function which depends on storm conditions (Hs, Tp and storm duration) and beach characteristics (sediment fall velocity and beach slope). This function was originally derived by using the Sbeach model (Larson and Kraus, 1989; Wise et al., 1996) for typical conditions on the Catalan coast (Mediterranean Sea). One of the points to be considered when applying this approach is that for this type of erosion, structural functions need to be calibrated for specific conditions of the study site. Another alternative for a simple erosion structural function is Kriebel and Dean's (Kriebel and Dean, 1993) convolution model. This is a simple analytical model predicting the time-dependent storm-induced beach profile response forced

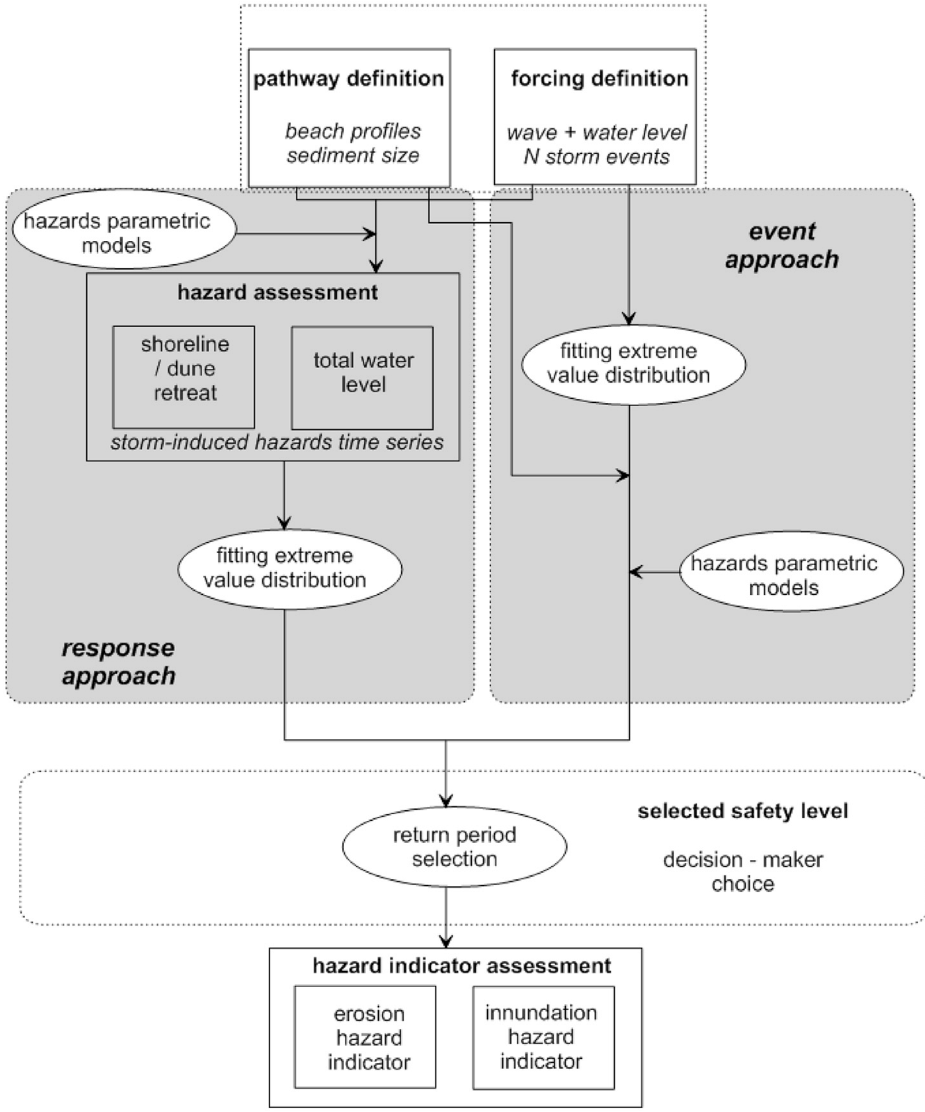


**Fig. 2.** Hazard assessment process in Phase 1.

by wave breaking and water level variation due to storm surge. This function has been used by Ferreira (2005) and Callaghan (Callaghan et al., 2013), among others, to obtain long-term time series of erosion hazards for coastal risk assessment.

Once the extreme probability distributions of the analysed hazards have been obtained, the final step is to compute the value of the corresponding hazard index for selected probabilities. To do this, computed hazard values are converted to flooding and erosion hazard scales. This is undertaken by taking into account the local characteristics of the processes and by ranging from 0 (smaller severity) to 5 (higher level of hazard). Table 2 shows an example of a scale for these hazards developed for risk analysis in the Catalan coast (Mediterranean Sea).

**Table 2**
Example of coastal flood and erosion hazard scales adopted for the Catalan coast (Mediterranean Sea) ($\Delta X_{10}$ is the storm-induced shoreline retreat associated with a return period of 10 years).

| Flooding extension (m) | Category | Beach width (W) after erosion (m) |
|---|---|---|
| > beach width + 60 m | 5 | beach fully eroded |
| ≤ beach width + 60 m | 4 | $W \leq \Delta X_{10}$ |
| ≤ beach width + 40 m | 3 | $\Delta X_{10} < W \leq 2\ \Delta X_{10}$ |
| ≤ beach width + 20 m | 2 | $2\ \Delta X_{10} < W \leq 3\ \Delta X_{10}$ |
| ≤100% beach width | 1 | $3\ \Delta X_{10} < W \leq 4\ \Delta X_{10}$ |
| ≤50% beach width | 0 | $4\ \Delta X_{10} < W$ |

### 3.4. Exposure assessment

The exposure indicators aim to answer the question "what is at stake?" within the potential hazard areas. However, using a common scale for different impacts (i.e. loss of assets and lands value, health and financial impacts on population, impacts on key infrastructures such as transport and utilities, and impact on the economy) might be problematic and challenging in such a screening approach, as the impacts vary in nature and cannot be easily expressed by the same unit. Therefore, each indicator is valued and ranked from 1 to 5 separately:

- Land Use: The Land Use Exposure Indicator compares the relative value of exposed assets and land along the coast. The type and the surface of land use can be derived from CORINE Land Cover[1] or from cadastral maps and using either market (Merz et al., 2010), economic valuation (Gopalakrishnan et al., 2009) or end-user preference valuation;

[1] http://www.eea.europa.eu/publications/COR0-landcover (accessed 30.11.2016).

- Population: The indicator is based on a Social Vulnerability Indicator (SVI) approach (Balica et al., 2012; Tapsell et al., 2002; Fekete, 2010; Cutter et al., 2013). The indicator considers differences between populations along the coast based on their socio-economic characteristics and can be derived from census data. Other existing regional or national indices such as depravation index can also be used;
- Transport, Utilities and Economic activities: these three impacts aim to better consider the exposure of assets leading to systemic impacts. At stake here are not only the exposed assets but also how a loss of these assets may lead to a higher order of losses (i.e. respectively traffic disruption, loss of services such as provision of water or electricity, loss or perturbation in a supply chain). The approach aims therefore to consider the exposed assets and their importance at different geographic scales (Table 3). Approaching key stakeholders, producing a schematic of the considered network and the locations of its key assets, and valuing their importance are the recommended approach (existing approaches (Armaroli and Duo, 2017; Jiménez et al., 2017; Alexandrakis et al., 2015; Alves et al., 2015, 2017) provide examples of valuation approaches to support such analysis for economic activities).

### 3.5. Phase 1 example of application: Ria Formosa

For the case of Ria Formosa (South Algarve, Portugal), the coastal index value was obtained for each kilometre sector along the barrier islands (Ferreira et al., 2016) for both overwash and erosion induced by storms. The hazards were calculated by using a 50 year return period, with the overwash being computed by using the Holman (1986) equation and the erosion with the Kriebel and Dean (1993) convolution model. Five exposure indicators were considered (Land Use, Population and Social Vulnerability, Transports, Utilities and Business) to generate the final Exposure Indicator. For the erosion coastal index most of the area is characterized by a similar, medium, index (Fig. 3), with only one area being defined as a hotspot: the central area of Praia de Faro, on the west flank of Ria Formosa. The rest of the sectors were characterized by CI values no higher than 3. Regarding the overwash coastal index two hotspots appear, Praia de Faro (as before) and Farol (Fig. 3) with the remaining CI values being around 3 or lower. The main reason for the low CI values is the limited exposure, with very low exposure indicators since the area is poorly occupied. The highlighted hotspots are within the few occupied areas of the system. The obtained hotspot (namely Praia de Faro) corresponds to the sectors that suffered more damages in the area in recent years because of the impact of storms, including the partial destruction of streets, houses, bars and restaurants.

## 4. CRAF phase 2: hotspots impact assessment and multi-criteria analysis

Depending on the variability in receptors and hazards along the coast, CRAF Phase 1 may identify multiple coastal sectors with high exposure to hazards. In CRAF Phase 2, hotspots are identified by grouping coastal sectors into distinct contiguous sets, typically of the order of 1–10 km in length along the coast, such that the hazard and impact at each hotspot location is independent of the hazard and impact at other hotspot locations, although the source of the hazard (e.g., storm surge) may correspond between hotspots. Hotspots may comprise heterogeneous geomorphic and socio-economic settings, allowing for a flexible application along the coast.

**Table 3**
Systemic exposure indicator values.

| Value | Rank | Description |
|---|---|---|
| 1 | None or Very Low | No significant network |
| 2 | Low | Mainly local and small network |
| 3 | Moderate | Presence of network with local or regional importance |
| 4 | High | High density and multiple networks of local importance or regional importance |
| 5 | Very High | High density and multiple networks of national or international importance |

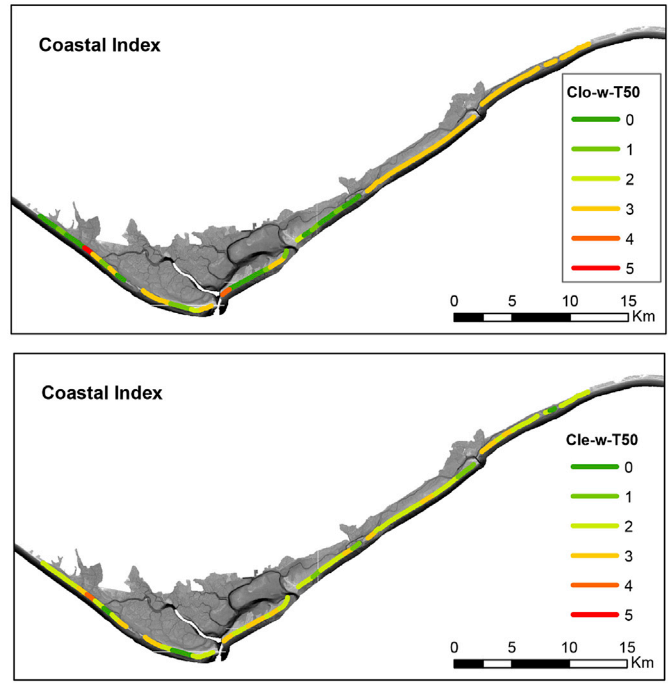


**Fig. 3.** Coastal indices distribution for Ria Formosa (Algarve, Portugal), for both overwash (upper panel) and storm induced erosion (lower panel).

CRAF Phase 2 is used to assess coastal risk at each hotspot location, and inter-compare the risk at these hotspots from a regional scale perspective. It is important to maintain the regional component of the assessment in Phase 2 as the approach considers systemic risk which can extend beyond the boundaries of the hotspot. This furthermore allows for effective comparison between hotspots and between indicators, as well as generally improving the regional risk assessment to enhance overall coastal decision-making. In CRAF Phase 2, the simple empirical hazard models of Phase 1 are replaced by process-based, multi-hazard models that are capable of accounting for morphodynamic feedback and the non-stationarity of storm events. Direct and indirect impacts at the hotspot, as well as systemic impacts in the region, are computed using high-resolution information on receptors in the region and the hazard extent (flooding, erosion, etc.) for each hotspot. CRAF Phase 2 allows the response approach for computing the return period of hazards adopted in Phase 1 to be maintained in the form of an extreme value distribution analysis of inundation discharge and shoreline erosion, or for a less computationally-expensive event-based approach to be adopted to compute coastal risk.

### 4.1. Hazard computation

The transformation from offshore forcing to coastal hazards in CRAF Phase 2 is achieved using a combination of high-resolution cross-shore transect models to compute coastal erosion, overtopping and overwash, and an area model to compute the flood extent in the hinterland, in a manner similar to Gallien (2016). To compute coastal erosion, overtopping and overwash, a set of cross-shore coastal transects ($P$; Fig. 4) is defined at each hotspot that captures the alongshore spatial variability in coastal geomorphology (e.g., beach width, dune height, seawall height) and offshore forcing (e.g., wave conditions), with a typical alongshore spacing in the order of tens of metres depending on the variability of the coastal morphology.

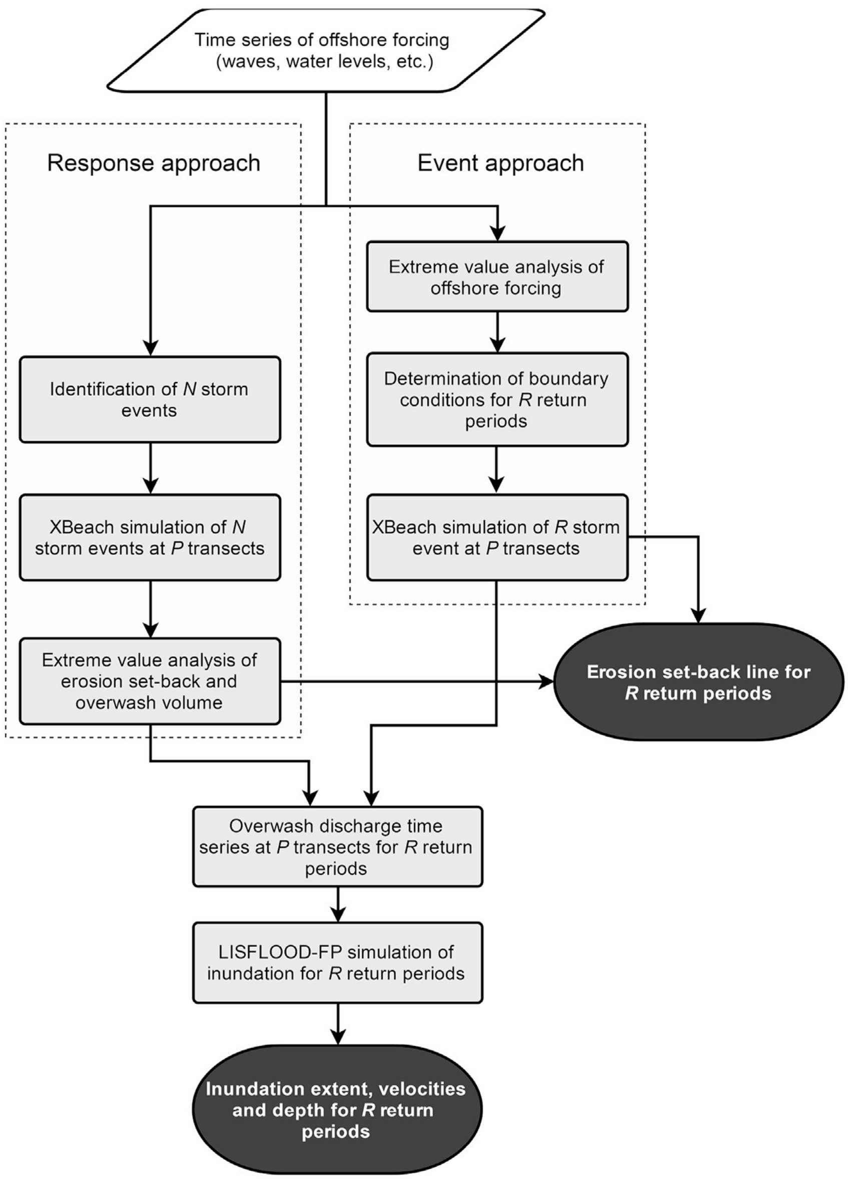


**Fig. 4.** Flow diagram of hazard computation in CRAF Phase 2.

In the response approach, a series of $N$ (Fig. 4) storm events is defined from the offshore wave and water level time series used in CRAF Phase 1 using a peak-over-threshold (POT) or annual maximum (AM) method. These storm events are simulated at the representative cross-shore transects of the hotspot using the open-source, multi-hazard storm impact model XBeach (Roelvink et al., 2009). This model has been selected due to its proven ability to capture storm hydro- and morphodynamics across a wide range of coastal environments (e.g (McCall et al., 2010; Dissanayake et al., 2014; De Vet et al., 2015; Smallegan et al., 2016).,). The 1D transect-version of XBeach is used in the CRAF to reduce computational expense relative to a 2DH approach, and allow for multiple simulations to be carried out at each hotspot, while retaining reasonable accuracy in the predicted morphodynamic response of the coast (Callaghan et al., 2013; Van Dongeren et al., 2009; Splinter et al., 2014). The simulated bed level changes, expressed in terms of shoreline retreat or beach and dune erosion volume, for every storm, can be fitted to an extreme probability distribution (e.g., generalized Pareto distribution when using POT to identify storms, or generalized extreme value distribution when using AM) to compute the predicted erosion set-back line corresponding to the desired return periods (Fig. 4) at every hotspot transect.

In addition to erosion, the XBeach model also simulates water discharges at the beach. This permits a consideration of how water discharge at the coast is affected by profile development during the storm (e.g., profile lowering during the impact of a given storm will increase the floodwater volume entering the hinterland during the event in comparison to the assumption of a static profile). The time series of storm-driven overtopping and overwash simulated by XBeach are furthermore used to compute the overwash volumes towards the hinterland relating to the return periods R. In this case, an extreme probability distribution is fitted to the alongshore-integrated overwash volume to compute the total volume reaching the hinterland for every return period. The predicted total overwash volume corresponding to a given return period is subsequently distributed according to the contribution of each representative profile to the total, and distributed in time according to the computed temporal variation of the simulated storm events, and finally provided as boundary conditions to an overland flood model of the event. The simulation of flooding is carried out using the hydrodynamic LISFLOOD-FP model (Bates and De Roo, 2000), which has been successfully employed to simulate inundation in fluvial and coastal areas (Bates et al., 2005; Purvis et al., 2008). The LISFLOOD-FP model provides time series of depth-averaged velocity and water depth at every model grid cell, with a spatial resolution in the order of 5–10 m, which can be used in the following step to compute the regional impact of each storm event.

In the case of the event approach, the return period of an event is based on an analysis of the offshore boundary conditions (e.g., wave height, surge level), rather than of the coastal hazards (e.g. erosion set-back and overwash volume). Therefore only one XBeach simulation is computed at every representative cross-shore transect per return period *R* of offshore boundary conditions (Fig. 4). The results of the simulation of these storm events are subsequently directly used to define the normative erosion set-backs and overwash volume relating to a given return period of offshore boundary conditions, and a LISFLOOD-FP model is used to compute hinterland flooding.

### 4.2. Impact computation

The INDRA (INtegrated DisRuption Assessment model) was specifically developed for CRAF Phase 2 in order to assess both direct and indirect impacts and to produce as outputs standardised indicators for a multi-criteria analysis (Viavattene et al., 2016). Eight types of indicators relating to the different categories of receptors are included measured (Fig. 5):

- Three indicators have been utilised to measure the range of impacts for the population, i.e., the potential risk to the population during an event, the displacement time and the household financial recovery following an event; • A business financial recovery indicator and a business disruption of supply chains indicator are considered for the impact on economic activities; • An ecosystem recovery indicator highlights potential changes to ecosystems; • A regional service transport disruption indicator value potential short and long term traffic impacts; and
- Up to 3 regional utility service disruption indicators can be used to consider potential change in the delivery of specific services (e.g., water, electricity).

A common five-point scale (None, Low, Medium, High and Very High Impacts) is used to measure the direct impacts from flood or erosion hazard obtained from XBeach1D – LISFLOOD-FP; each scale being associated with a threshold level. This approach was preferred to reduce issues of inconsistency units (such as for tangible and intangible in economic assessment) and of data collection and availability between case studies and between the type of impacts (Jongman et al., 2012; Merz et al., 2010; Meyer et al., 2009; Viavattene et al., 2014). The approach aims to increase flexibility and the ease of use as scarce or rich data can be utilised. However, to maintain a degree of transparency and an opportunity to improve the assessment, a Data Quality Score is included in the approach. It consists of scoring between 1 and 5 the different input data (From "1 - Data available and of sufficient quality" to "5 - No data available, based on multiple assumptions"). Finally a scalar method was considered appropriate as it supports a comparative approach sufficient to highlight major differences in impacts; the objective not being here to quantify losses absolutely but to compare them. The threshold levels are derived from established vulnerability assessment methods (Table 4) (Viavattene et al., 2015b).

Assessing indirect impact requires a consideration of the change in flows rather than a loss of stocks as well as the inclusion of a temporal dimension to the analysis (Rose, 2010). However, there is a current lack of data and methodologies developed which associated direct and indirect losses (Penning-Rowsell et al., 2013; Messner et al., 2007; Przyluski and Hallegatte, 2011). INDRA aims to fill this gap and adopts approaches to indirect loss assessment which utilises direct impacts as an input variable (see Fig. 5). To meet research and practical needs three techniques have been considered depending on available knowledge, data and resources.

In the susceptibility-based approach the score is derived automatically from the direct impact assessment. The indirect impacts are included in the considered methods, with the direct impact being used as a proxy. This is the case for risk to life and ecosystem. For instance, the outcomes are expressed in terms of potential change and recovery period for the ecosystems (Zanuttigh et al., 2014) – in the case of salt marshes their locations (i.e. open coast, estuary, back barrier), the tidal range, the water depth and the wave height are considered as key factors to estimate the level of changes (see Table 5).

In the matrix-based approach an indirect impact value is associated

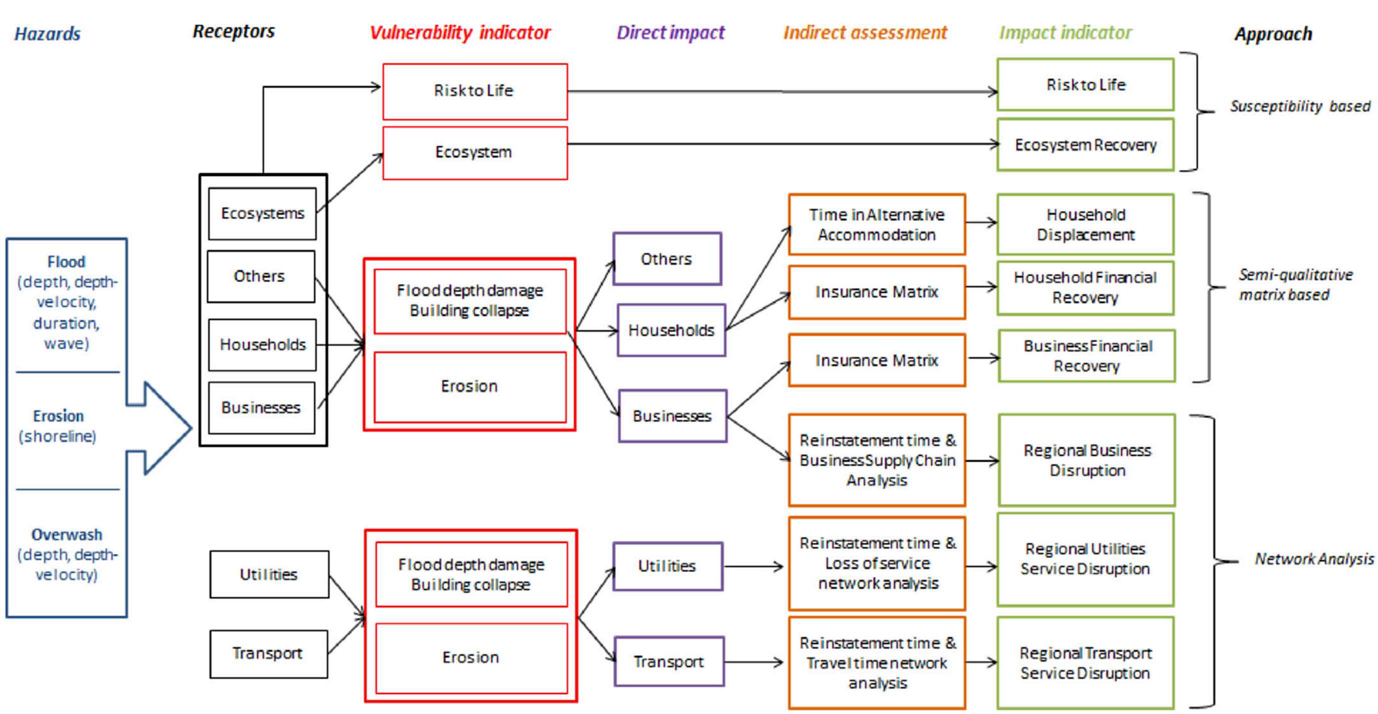


Fig. 5. Impact assessment process.

**Table 4**
Direct impacts, hazard and vulnerability for different categories.

| Category | Direct impacts | Hazard intensities (main) | Vulnerability indicators | References |
|---|---|---|---|---|
| Built Environment | Inundation damages | Flood depth, Duration | Depth-damage curves | (Jongman et al., 2012; Penning-Rowsell et al., 2013; Merz et al., 2010) |
| | Collapse | Flood depth-velocity | Risk matrix | (Karvonen et al., 2000) |
| | Evacuation and collapse | Erosion distance shoreline | Distance-based approach | (Ciavola et al., 2011) |
| Population | Risk to life | Flood depth-velocity | Risk matrix | (Priest et al., 2007; Tapsell et al., Penning-Rowsell) |
| Ecosystems | Change in habitats | Duration, depth, sedimentation | Impact scale | (Zanuttigh et al., 2014) |

**Table 5**
Ecosystem Impacts for Salt Marshes (from Viavattene et al. (2015b).

**Open coast marshes in microtidal areas (tidal range < 2 m)**

| | Wave height (m) | | | | |
|---|---|---|---|---|---|
| Water depth (m) | < 0.3 | 0.3 to 0.6 | 0.6 to 1 | 1 to 2 | > 2 |
| 0 to 1 | 0 | 3 | 3 | 3 | 3 |
| 1 to 2 | 0 | 2 | 3 | 3 | 3 |
| 2 to 3 | 0 | 1 | 2 | 3 | 3 |
| 3 to 4 | 0 | 0 | 1 | 2 | 3 |

**Indicator scale:**

0 no effect
1 changes within normal seasonal variation
2 changes beyond normal seasonal variation but partial/total recovery
3 irreversible change

with a direct impact scale. Such an approach is used for household displacement, and household and business financial recovery. Specific novel methodologies have been developed based on a semi-qualitative matrix approach to establish these values. The household displacement value is calculated using a matrix distributing, for each impact level, the proportion of households being displaced for different durations (Table 6). A separate matrix for businesses and households permits an estimation of the likely degree of financial recovery through combining direct impact information (i.e. the severity of the event) with the presence or absence of a series of financial recovery mechanisms (including government compensation, government and private-market insurance, tax relief, charitable assistance, welfare relief) and utilises a score from 1 to 5 (full financial recovery to very low financial recovery). The user is required to distribute the households/businesses with each type of financial mechanism utilising existing or new survey data.

A third approach has been developed to allow the assessment of indirect impacts associated with networks (transports, utilities and business supply chain) and to avoid either the too simplified option of using proxy values based on empirical analysis, which are also difficult to transfer from one case to another, or the too challenging and complex flow modelling techniques (Meyer et al., 2013; Viavattene et al., 2016; Merz et al., 2010; Rose, 2010). Network analysis, which is faster and less data-demanding, was selected as the best approach. In each case the network is represented by a set of nodes (road junction, business tier, and services production and distribution assets) and by a set of links between the nodes (roads, supply link, distribution lines). The assessment considers changes in the structural properties of the network over time following an event considering the reinstatement time of individual impacted nodes and links and derives indicators using network analysis concepts (e.g. connectivity, shortest pathways, degree of centrality, closeness) (Tanenbaum, 1981). For the transport category, the indicators combine a Connectivity Ratio and a Time Ratio. The Connectivity Ratio gives information on the loss of connectivity between locations. The Time Ratio aims to represent the scale of increased travel time from one location to another. For utilities, the indicator combines a connectivity loss ratio (e.g., percentage of loss of connection to a source) and an imbalance value (i.e. the demand exceeds the supply). For businesses the indicator assesses the reduction in the supply capacity of each of its economic tiers weighted by their relative economic importance.

### 4.3. Multi-criteria analysis and hotspot selection

In order to rank and reach a consensus on the selected hotspot(s), the various indicators need to reflect the perspectives of various stakeholders. A Multi-Criteria Analysis (MCA) is considered here as an appropriate and widely used approach support transparent decision-making between various stakeholders (Meyer et al., 2009; Dunning et al., 2000; Brown et al., 2001; Levy, 2005; Mendoza and Martins, 2006; Huang et al., 2011; Papaioannou et al., 2015). Of the various MCA techniques available, the CRAF uses a multi-attribute decision-making approach with weighted summation to score the different hotspots by transforming all criteria onto a commensurable scale, multiplied by weights and finally summed to attain an overall utility (Hajkowicz and Higgins, 2008). In CRAF Phase 2 each criterion values the impact indicators from a regional scale perspective (Table 7) and is scaled from 0 to 1 (no impact to full impact). For household displacement, and household and business financial recovery, every household and business in the region are scored from 0 to 5 (0 no impact to 5 worst impact); the standardisation consists in the summation of all the property scores versus a worst case scenario (all properties impacted at a level 5). The same principle is used for risk to life and ecosystems but is based on the land use area. For the regional business, transport and utility disruption the standardisation is already included within the indicator calculation at every time step of the simulation and simply requires integration over time. Each criterion can be weighted by the stakeholders to express their preference using a value between 0 and 100, the total of the weights being equal to 100.

**Table 6**
Example of distribution of household properties and scores for different recovery mechanisms and flood damage direct impact in North Norfolk.

| Financial Recovery Mechanism | Distribution of total population (%) | Financial Recovery Matrix Score | | | |
|---|---|---|---|---|---|
| | | Low Impact | Medium Impact | High Impact | Very High Impact |
| No Insurance | 12 | 2 | 3 | 4 | 5 |
| Self-Insured | 2 | 1 | 2 | 3 | 4 |
| Small Govt. compensation | 0 | 1 | 2 | 3 | 4 |
| Large Govt. compensation | 0 | 1 | 1 | 2 | 3 |
| Partly-Insured | 21 | 1 | 2 | 3 | 4 |
| Fully-Insured | 65 | 1 | 1 | 1 | 2 |

**Table 7**
Indicators and standardisation process.

| Criteria | Standardisation | Variables |
|---|---|---|
| Household displacement | $\frac{\sum_{i=0}^{n} Hd_i}{\sum_{i=0}^{n} 5}$ | n = number of household property<br>Hd = displacement score for each household property (0–5) |
| Household financial recovery | $\frac{\sum_{i=0}^{n} Hfr_i}{\sum_{i=0}^{n} 5}$ | n = number of household property<br>Hd = financial score for each household property (0–5) |
| Business financial recovery | $\frac{\sum_{i=0}^{n} Hfr_i}{\sum_{i=0}^{n} 5}$ | n = number of business property<br>Hd = financial score for each business property (0–5) |
| Regional Business Disruption | $\frac{\sum 1-\frac{1}{\sum We} \sum_{i=1}^{d}\left(We_i * \frac{Cimp_i}{Cnorm_i}\right)}{t}$ | t = simulation time<br>d = tier node<br>We = economic importance of a tier node<br>Cimp = capacity of a tier node after the event<br>Cnorm = capacity of a tier node before the event |
| Ecosystem recovery | $\frac{\sum_{i-0}^{n} (S_i * EVI_i)}{\sum_{i=0}^{n} (S_i * 4)}$ | n = number of ecosystem land use<br>S = ecosystem area<br>EVI = ecosystem impact score (0–4) |
| Risk to life | $\frac{\sum_{i-0}^{n} (S_i * RtL_i)}{\sum_{i=0}^{n} (S_i * 4)}$ | n = number of land use with presence of population<br>S = land use area<br>RtL = ecosystem impact score (0–4) |
| Regional Utilities Disruption | $\frac{\sum_{i=0}^{t} (ICl * Isl)}{t}$ | t = simulation time<br>Icl = percentage of connectivity loss<br>Isl = Imbalance between demand and supply |
| Regional Transport Disruption | $\frac{\sum_{i=0}^{t} \frac{\mathrm{WDimpi}}{\mathrm{WDnormi}} \times \frac{\mathrm{TLnormi}}{\mathrm{TLimpi}}}{t}$ | t = simulation time<br>WDimp connectivity after the event<br>WDnorm connectivity before the event<br>TLimp Time lengthening after the event<br>TLnorm Time lengthening after the event |

### 4.4. Phase 2 example of application: the North Norfolk coast

For the English North Norfolk case study (see Christie et al., 2017 for more details) two hotspots, (Wells and Brancaster) were compared. The hazards were calculated using XBeach on 41 transects for Brancaster and 58 for Wells for a 1 in 115 year return period storm event (return period representative of the 2013 extreme surge event). The flood intensities were generated with a 2D LISFLOOD-FP model using a grid of 200 m*200 m resolution. Eight impacts indicators were considered in the assessment (*Risk to life, Household Financial Recovery, Household Displacement, Business Financial Recovery, Business Disruption, Natural Ecosystem, Agriculture* and *Transport Disruption*) (Table 8). The Data Quality Scores obtained were either 2 (Data available but with known deficiencies) or 3 (No data available/poor data use of generic data but representative enough to compare the hotspots). Three groups were represented for weighting the MCA by expert judgment (Neutral preference, preference for household and business, preference for ecosystem), the maximum weighing for an indicator never exceeding 35 of 100. If the household and business are preferred, Wells obtained a higher score with the business disruption indicator balancing the score in favour of Wells. In the other cases Brancaster is clearly the potential hotspot, where the score is largely influenced by the ecosystem impact indicator. The Data Quality Score for both being of 3, improvement should be expected and prioritized for calculating the ecosystem and the business disruption indicators.

## 5. Discussion

The Coastal Risk Assessment Framework was applied on 10 different regional coastal cases in Europe (e.g., Sweden, Germany, Belgium, England, France, Portugal, Spain, Italy (2), and Bulgaria) by various research teams in collaboration with their local end users. Such diversity of applications allows the testing of the approach in different coastal environments; not only in different in terms of physical and socio-economic characteristics but also in various scientific and cultural contexts.

The Coastal Index framed the application by providing a few rules (e.g., a similar assessment per sector, the use of response approach if possible, the type of indicators and their valuation) to maintain consistency in the analysis. However, the limited rules provided in the CRAF Phase 1 provide sufficient flexibility for the user to choose the best available method and data to perform the regional analysis. As such, the response approach was used on the majority of the cases where large data sets of measures or hindcast data exist and different empirical models were used or adapted (e.g., Holman (1986) or Stockdon et al. (2006). for run-up level, the simplified Donnely (Donnelly, 2008) for overwash extent; Hedges and Reis (1998) or EurOtop for overtopping (Pullen et al., 2007), Kriebel and Dean (1993), Mendoza and Jiménez (2006) for storm-induced beach erosion). In certain cases, due to the complexity of the coast and a lack of existing skills and resources, less simplified approaches such as X-Beach 1D model were preferred. Similarly, for estimating the hazard extent approaches were varied, ranging from the

**Table 8**
Impact assessment results for North Norfolk case study (adapted from Christie et al., 2017).

| Category | Data source | Data Quality Score | Wells Score ($10^{-4}$) | Brancaster Score ($10^{-4}$) | Range of MCA Weight |
|---|---|---|---|---|---|
| Risk to life | National receptor dataset | 3 | 8.3 | 0.9 | 12.5–35 |
| Household Financial Recovery | Office for National Statistic and insurance penetration data | 2 | 1.4 | 0.8 | 5–12.5 |
| Household Displacement | Insurance claims data | 2 | 1.3 | 1.1 | 5–15 |
| Business Financial Recovery | Insurance penetration data | 3 | 9.1 | 0 | 5–15 |
| Business Disruption | Tourism industry (grey literature and local experts) | 3 | 22.5 | 0 | 5–12.5 |
| Natural Ecosystem | Land cover data (Freshwater grazing marsh and salt marsh) | 3 | 31.6 | 136.4 | 5–20 |
| Agriculture | Land cover data (Mainly winter cereals) | 3 | 0.3 | 11.2 | 5–12.5 |
| Transport Disruption | National transport data | 2 | 24.9 | 0 | 10–20 |

simple use of a buffer zone approach to fast 2D flood solver techniques.

Clear differences in assessing the exposure indicators were revealed by their applications within the case studies. Information on land use, population (e.g. census data) and transport are commonly available. Where the European dataset CORINE Land Cover was proposed for the land use valuation, a more detailed cartography map was used in most cases. Local transport maps were also preferred. Although existing social vulnerability indicators were predominantly not available, national census data permitted the development of a social vulnerability indicator without difficulty. An additional, general issue was that the scale of information was often too low to permit a clear discrimination between coastal sectors. The economic activities indicator was not so straightforward. It required an investigation of the specific regional economic context and its important economic activities. As such, the development of case specific evaluation approaches was required including if possible, the involvement of stakeholders (e.g., tourist information and businesses locations when focusing on one specific sector such as tourism, economic sector indicators when a range of economic activities are at stake). Defining the exposure and importance of utility assets and their services remained a challenging task and was often based on expert judgments or a quick survey assessment due to the absence of network maps and/or difficulties in accessing restricted information. As a result this indicator remains tentative in many case studies. For all indicators the involvement of the stakeholders was a key process to gather information, improve the indicators valuation and increase the confidence in the index approach. Overall it should also be noted that the coastal analysis benefited to be within the “regional” administration avoiding the comparison of indicators produced from heterogeneous sources of data.

It was also critical to involve stakeholders in the definition of the coastal index return periods to be considered and therefore a variety of return periods were selected ranging from 10 to 100 years for most case studies (unprotected coasts), and up to 1000 years for protected coasts. It should be noted that there is more confidence in the results for lower return periods due to the higher quality of the time series. Furthermore, the use of both a worst case scenario and an average scenario as well as the use of different return periods acts as a counterbalance to the simplicity of the approach and facilitates the identification of hotspots with the stakeholders.

Validation was performed using historical information, existing evaluation and local expertise (the Italian Emilia-Romagna case study is a good example (Armaroli and Duo, 2017)). 22 costal indices were produced across different regional case studies. In some case studies at least two coastal indices were calculated to represent different hazards, mainly flooding and erosion. In some cases, different return periods were also tested. 18 indices scored high specific coastal sectors which correspond to coastal zones identified as known hotspots and no known hotspots by the end users remained unidentified. Slight deviations in hotspot location were reported but no major deviations were recognised. Validation was difficult in some cases due to differences between very recent changes to coastal management protection defences and the use of historical records. Main limitations in the approach appeared when adopting a simplified approach or by the use of one profile per sector to represent a complex coastal system and its hinterland. In such cases, an improvement would be to apply the coastal index with smaller sectors to better capture specific profiles of the coastline and to use the worst case scenarios rather than the average scenarios to perform the identification. Another option is to lower the threshold of identification and to perform CRAF Phase 2 analysis on a greater number of potential hotspots.

In most regional case studies, two hotspots identified in Phase 1 were compared in Phase 2. The coupled 1D XBeach and LISFLOOD models were applied on most case studies although variations between case studies were observed in the choice of profiles and elevation grid resolution (up to 10 m*10 m). However, conceivably any other fast and efficient dynamic flood solver could be used (for instance the numerical modelling system SELFE was preferred by the French Case study (La Faute-sur-Mer)). Dynamic models were preferred to static models in order to avoid the potential for overestimation and, in some cases, underestimation of flood extent (Orton et al., 2015). Based on the recommendation in Vousdoukas et al. (2016). the method of calculation of the inundation has been extended by including the XBeach model wave effects on the total water level, including wave run-up and overwash, and the morphodynamic response of the coast.

Improvement in hazard intensities assessment may only benefit risk assessment if sufficient data are available to assess the exposure and the various impacts. In most regional case studies it was possible to access information on the georeferenced location of the land uses. Nevertheless, detailed information about the receptors' characteristics and their associated susceptibility was unavailable and the robustness of the assessment might only have been improved by detailed additional surveys to gain additional knowledge. By default, therefore, generic property types (e.g. residential and non-residential properties) and vulnerability curves were used for an initial assessment. The use of simplified impact thresholds facilitates a direct impact assessment in data poor environments; yet detailed data should be sought if necessary.

Similar results were observed for the indirect indicators. Table 9 provides the data quality scores obtained for each indicator from the case studies. However, despite the provision of a standardised quality score classification, each case study may have a slightly different perception of data quality. It is important to recognise, however, that data quality scores may be case specific and also reflect the stakeholder participation processes within the CRAF. Therefore, no proper harmonisation of the data quality scores have been performed between the case studies; and there is a need to be cautious when comparing results, however we consider that the following lessons can be learned.

Most of the indicators were assessed with generic data considered representative or available for the regional or national scale but with known deficiencies. For the risk to life indicator only one case was reportedly able to perform an assessment with sufficient data, as research was performed on the area following a recent catastrophic event, otherwise other case studies referred to a generic existing risk to life matrix provided by a previous European research project ((Tapsell et al., Penning-Rowsell)). For household displacement, the lack of evidence to support the analysis was particularly stressed due to the lack of surveyed evidence and/or of recent dramatic events. Both financial recovery indicators were based on national policy figures and applied uniformly for all receptors in the region; except for the English case where sub-regional differentiation was possible. This lack of data limits the potential to compare hotspots on financial recovery and socio-economic differences rather than on the simple consideration of direct impacts. Sufficient data were available and accessible for evaluating transport service disruption as it only requires the mapping of the regional network and an evaluation of the different locations. However, data were lacking on road elevation and on the susceptibility thresholds, and therefore in both cases generic values were used. The degree of subjectivity in valuing the importance of locations was also questioned in some cases. Very simple business supply chains were used to assess business disruption and difficulties in gathering homogeneous and sufficient information to support the assessment were recognised. The approach remained complex and difficult to apply for most of the users. Further research as well as the need for better data collection was clearly identified for this indicator. Mixed data quality scores were obtained for the ecosystems assessment and only one case applied the utility services disruption indicator, therefore additional applications on other cases are necessary to provide an evaluation of these approaches.

The contribution of the different indicators to the total hotspot score varies between case studies highlighting differences in socio-economic context of the different regions. The percentage contribution of each indicator to the total hotspot score has been calculated for each hotspot and the indicators contributing more than 20% are reported in Table 10. In general two or three indicators dominate the final result and, therefore, an improvement of the data quality score associated with these indicators should be prioritized. For certain regional case studies if

**Table 9**
Distribution of case studies data score quality per indicator (all indicators are not necessarily assessed in a case study).

| Data Quality | Data available of sufficient quality | Data available but with known deficiency | No data available/poor data Use of generic data but representative enough | No data available/poor data Use of generic data but likely not representative | No data available, multiple assumption |
|---|---|---|---|---|---|
| Risk to Life | 1 | 0 | 8 | 1 | 0 |
| Ecosystems | 0 | 1 | 2 | 1 | 1 |
| Household Displacement | 0 | 1 | 5 | 2 | 2 |
| Household Financial Recovery | 0 | 4 | 4 | 1 | 1 |
| Businesses Financial Recovery | 0 | 4 | 3 | 1 | 2 |
| Regional Business Disruption | 0 | 0 | 4 | 1 | 2 |
| Regional Utilities Service Disruption | 0 | 1 | 0 | 0 | 0 |
| Regional Transport Service Disruption | 0 | 8 | 0 | 0 | 0 |
| Total | 1 | 19 | 26 | 7 | 8 |

**Table 10**
**Prevailing indicators in the selection process per regional case study**.

| | Number of dominant indicators (>20% of the total score for one hotspot) | Indicators | Different indicators between hotspots |
|---|---|---|---|
| NorthForfolk | 2 | RisktoLife, Natural Ecosystems | No |
| Emilia-Romagna | 1 | Business disruption | No |
| Kiel | 4 | RisktoLife, Natural Ecosystems, business financial recovery, transport | Yes |
| Belgium | 4 | Household displacement, household financial recovery, business disruption, transport | No |
| Ria Formosa | 2 | Household displacement, business disruption | Yes |
| Kristianstad | 2 | Business disruption, household financial recovery | Yes |
| Varna | 1 | Business disruption | No |
| Liguria | 3 | Household and Business financial recovery, business disruption | Yes |
| Catalan Coast | 3 | Business financial recovery, business disruption, transport | Yes |
| Faulte sur Mer | 3 | Risk to life, business financial recovery, transport | No |

significant differences in land use exist between hotspots, indicators may dominate in one hotspot and not the other. This information is reported in the last column of Table 10 and highlights that two situations may occur. The same indicators are considered for comparing the identified hotspots. Such a situation reduces conflict in decision-making as a common assessment approach is used and stakeholders may have agreed on similar weighting within the MCA. In such cases robustness can be improved by identifying and reducing uncertainties on the major differences between the two hotspots for the considered indicator. In other situations, whereby different indicators dominate between identified hotspots, the selection of the critical hotspot may be inhibited by poor data quality and incomparability of the assessment. Although the cases of Kiel, Ria Formosa, Kristianstad, Liguria and the Catalonian coast are illustrative of multiple dominant indicators, hotpot selection was possible in these situations as one hotspot score always clearly outranked the others. Indeed in all ten regional case studies the users validated the results obtained using CRAF Phase 2.

## 6. Conclusion

The CRAF supports decision-makers by providing them with a framework, with associated guidance documents and models, with which to screen the regional coast in the identification and selection of hotspots where detailed modelling and risk reduction measures should be considered. The framework is flexible enough to be applied in various geomorphological and socio-economic contexts, and in data-poor and data-rich situations. A two-step approach has been chosen to allow fast and efficient scanning of large sections of the coast and as well as for incorporating novelties and required changes for a better integrated and systemic risk assessment. Key benefits and novelties of the framework include its multi-hazard assessment capacity, the consideration of the probability of hazards that affect receptors (e.g., erosion and flooding) rather than the meteorological and marine boundary conditions leading to the hazard (e.g., offshore wave height and surge), the assessment of indirect and systemic impacts and the inclusion of a recovery period analysis.

Phase 1 provides a framework for a traditional screening approach that generates sectorial coastal indicators and is aimed at identifying higher risk areas. The CRAF recommends the use of a response approach, except in the case of significant lack of long time series of forcing conditions and simple empirical models to compute the hazard. In Phase 1, the impact assessment is deliberately restricted to the presence and importance of receptors but includes an evaluation of regional networks to better consider potential systemic effects.

Phase 2 is the most innovative component of the framework, addressing challenging issues in coastal risk assessment, including the consideration of multi-hazards, morphodynamic feedback, non-stationarity of storm-events as well as systemic impacts. The hotspots are compared using a Multi-Criteria Analysis from a regional scale perspective, incorporated in the impact assessment model (INDRA) developed for this purpose. The methods for assessing the indicators were developed considering potential data availability, complexity of the techniques and limitation of resources. In particular INDRA includes innovative assessment techniques based on network analysis and a semi-qualitative matrix approach.

The CRAF also offers the possibility of involving stakeholders at different stage of the process. As such it allows a comprehensive research and knowledge-based discussion on the selection of hotspots, in which the quantitative results and stakeholder engagement is combined to provide impact outcomes. Engaging with stakeholders can support the collection of information, the valuation of assets at risk, the weighting of criteria and the co-validation of the results. The framework was developed as such that a learning process is involved allowing a common understanding of the limitations and a critical analysis of the results achieved. Furthermore, the CRAF also supports an evaluation of necessary efforts in future data collection in particular by the use of a Data Quality Score. While sufficiently flexible to be applied in data-poor situations, the CRAF Data Quality Score provides insight into the effect of uncertainties in the risk evaluation and hotspot ranking due to lack of data, or low confidence in existing datasets, and can thus be used by coastal managers to assess their confidence in coastal management decisions and prioritise the collection of the most relevant data.

The CRAF has been developed and tested within the RISC-KIT project as a prototype and further research and development will be required in particular for Phase 2. A fully integrated approach is still required to assess the probability of occurrence, i.e. the inclusions of the consequences in the response approach. Certain impacts are not fully considered in the INDRA model such as cascading effects between different networks, impacts on public services, or the health impacts. Further research should be sought to examine the potential for the stakeholders' involvement and to investigate the influence of the different standardisation techniques and the MCA on the final results and the selection process. Limitations in the use of the framework are inherent to the lack of data, such as long-term datasets for the response approach, surveys on insurance penetration or recovery time, and detailed information on networks (e.g. business supply chain, critical infrastructure).

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## References

Alexander M., Doorn N., Priest S.J., “Through the looking glass” - Searching for theoretical and practical clarity on how to deliver legitimate flood risk governance, *Reg. Environ. Chang.* (2017).

Alexandrakis, G., Poulos, S.E., 2014. An holistic approach to beach erosion vulnerability assessment. Sci. Rep. 4 http://dx.doi.org/10.1038/srep06078, 6078.

Alexandrakis, G., Manasakis, C., Kampanis, N.A., 2015. Valuating the effects of beach erosion to tourism revenue. A management perspective. Ocean. Coast. Manag. 111, 1–11. http://dx.doi.org/10.1016/j.ocecoaman.2015.04.001.

Alves, B., Rigall-I-Torrent, R., Ballester, R., Benavente, J., Ferreira, Ó., 2015. Coastal erosion perception and willingness to pay for beach management (Cadiz, Spain). J. Coast. Conserv. 19, 269–280. http://dx.doi.org/10.1007/s11852-015-0388-6.

Alves, B., Ballester, R., Rigall-I-Torrent, R., Ferreira, Ó., Benavente, J., 2017. How feasible is coastal management? A social benefit analysis of a coastal destination in SW Spain. Tour. Manag. 60, 188–200. http://dx.doi.org/10.1016/j.tourman.2016.12.004.

De Angeli S., D'Andrea M., Cazzola G., Rebora N., Coastal Risk Assessment Framework: comparaison of fluvial and marine inundation impacts in Bocca di Magra, Italy, Coast. Eng. (2017).

Armaroli C., Duo E., Validation of the Coastal storm Risk Assessment Framework along the Emilia-Romagna coast, Coast. Eng. (2017).

Balica, S.F., Wright, N.G., van der Meulen, F., 2012. A flood vulnerability index for coastal cities and its use in assessing climate change impacts. Nat. Hazards 64, 73–105. http://dx.doi.org/10.1007/s11069-012-0234-1.

Barquet K., Dickin S., Meijer J., Dastgheib A., Piloting RISC-KIT's integrated approach for assessing Disaster Risk Reduction measures in the coast of Kristianstad, Sweden, Coast. Eng. (2017).

Bates, P., De Roo, A.P., 2000. A simple raster-based model for flood inundation simulation. J. Hydrol. 236, 54–77. http://dx.doi.org/10.1016/S0022-1694(0000278-X).

Bates, P.D., Dawson, R.J., Hall, J.W., Horritt, M.S., Nicholls, R.J., Wicks, J., Hassan, M.A.A.M., 2005. Simplified two-dimensional numerical modelling of coastal flooding and example applications. Coast. Eng. 52, 793–810. http://dx.doi.org/10.1016/j.coastaleng.2005.06.001.

Bogaard T., De Kleermaeker S., Jaeger W.S., Development of generic tools for coastal forecasting and warning, Coast. Eng. (submitted).

Bosom, E., Jiménez, J.A., 2010. Storm-induced coastal hazard assessment at regional scale: application to Catalonia (NW Mediterranean). Adv. Geosci. 26, 83–87.

Bosom, E., Jiménez, J.A., 2011. Probabilistic coastal vulnerability assessment to storms at regional scale – application to Catalan beaches (NW Mediterranean). Nat. Hazards Earth Syst. Sci. 11, 475–484. http://dx.doi.org/10.5194/nhess-11-475-2011.

Brown, K., Adger, W.N., Tompkins, E., Bacon, P., Shim, D., Young, K., 2001. Trade-off analysis for marine protected area management. Ecol. Econ. 37, 417–434. http://dx.doi.org/10.1016/S0921-8009(0000293-7).

Callaghan, D.P., Nielsen, P., Short, A., Ranasinghe, R., 2008. Statistical simulation of wave climate and extreme beach erosion. Coast. Eng. 55, 375–390. http://dx.doi.org/10.1016/j.coastaleng.2007.12.003.

Callaghan, D.P., Ranasinghe, R., Roelvink, D., 2013. Probabilistic estimation of storm erosion using analytical, semi-empirical, and process based storm erosion models. Coast. Eng. 82, 64–75. http://dx.doi.org/10.1016/j.coastaleng.2013.08.007.

Carrera, L., Standardi, G., Bosello, F., Mysiak, J., 2015. Assessing direct and indirect economic impacts of a flood event through the integration of spatial and computable general equilibrium modelling. Environ. Model. Softw. 63, 109–122. http://dx.doi.org/10.1016/j.envsoft.2014.09.016.

Cristie E., Spencer T., Owen D., McIvor A., Moller I., Viavattene C., Regional coastal flood risk assessment for a tidally dominant, natural coastal setting: North Norfolk, southern North Sea, Coast. Eng. (2017).

Ciavola, P., Ferreira, O., Haerens, P., Van Koningsveld, M., Armaroli, C., 2011. Storm impacts along European coastlines. Part 2: lessons learned from the MICORE project. Environ. Sci. Policy 14, 924–933. http://dx.doi.org/10.1016/j.envsci.2011.05.009.

Corbella, S., Stretch, D.D., 2012. Predicting coastal erosion trends using non-stationary statistics and process-based models. Coast. Eng. 70, 40–49. http://dx.doi.org/10.1016/j.coastaleng.2012.06.004.

Cutter, S.L., Emrich, C.T., Morath, D.P., Dunning, C.M., 2013. Integrating social vulnerability into federal flood risk management planning. J. Flood Risk Manag. 6, 332–344. http://dx.doi.org/10.1111/jfr3.12018.

Demirel, H., Kompil, M., Nemry, F., 2015. A framework to analyze the vulnerability of European road networks due to Sea-Level Rise (SLR) and sea storm surges. Transp. Res. Part A Policy Pract. 81, 62–76. http://dx.doi.org/10.1016/j.tra.2015.05.002.

Dissanayake, P., Brown, J., Karunarathna, H., 2014. Modelling storm-induced beach/dune evolution: sefton coast, Liverpool Bay, UK. Mar. Geol. 357, 225–242. http://dx.doi.org/10.1016/j.margeo.2014.07.013.

Divoky, D., McDougal, W.G., 2007. Response-based coastal flood analysis. In: Coast. Eng. 2006. World Scientific Publishing Company, pp. 5291–5301. http://dx.doi.org/10.1142/9789812709554_0443.

Van Dongeren, A., Bolle, A., Vousdoukas, M.I., Plomaritis, T., Eftimova, P., Williams, J., Armaroli, C., Idier, D., Van Geer, P., Van Thiel de Vries, J., Haerens, P., Taborda, R., Benavente, J., Trifonova, E., Ciavola, P., Balouin, Y., Roelvink, D., 2009. MICORE: dune erosion and overwash model validation with data from nine European field sites. In: Proc. Coast. Dyn. 2009, WORLD SCIENTIFIC, pp. 1–15. http://dx.doi.org/10.1142/9789814282475_0084.

van Dongeren, A., Ciavola, P., Viavattene, C., de Kleermaeker, S., Martinez, G., Ferreira, O., Costa, C., McCall, R., 2014. RISC-kit: resilience-increasing Strategies for coasts - toolKIT. J. Coast. Res. 366–371.

Donnelly, C., 2008. Coastal Overwash: Processes and Modelling. University of Lund.

Driessen, P.P.J., Hegger, D.L.T., Bakker, M.H.N., van Rijswick, H.F.M.W., Kundzewicz, Z.W., 2016. Toward more resilient flood risk governance. Ecol. Soc. 21, art53 http://dx.doi.org/10.5751/ES-08921-210453.

Dunning, D.J., Ross, Q.E., Merkhofer, M.W., 2000. Multiattribute utility analysis for addressing section 316(b) of the clean water act. Environ. Sci. Policy 3, 7–14. http://dx.doi.org/10.1016/S1462-9011(0000022-8).

Eusgeld, I., Kröger, W., Sansavini, G., Schläpfer, M., Zio, E., 2009. The role of network theory and object-oriented modeling within a framework for the vulnerability analysis of critical infrastructures. Reliab. Eng. Syst. Saf. 94, 954–963. http://dx.doi.org/10.1016/j.ress.2008.10.011.

Fekete, A., 2010. Assessment of Social Vulnerability for River-floods in Germany. United Nations University – Institute for Environment and Human Security.

Ferreira, Ó., 2005. Storm groups versus extreme single storms: predicted erosion and management consequences. J. Coast. Res. 42, 155–161.

Ferreira, O., Viavattene, C., Jiménez, J., Bole, A., Plomaritis, T., Costas, S., Smets, S., 2016. CRAF Phase 1, a framework to identify coastal hotspots to storm impacts. E3S Web Conf. 7, 11008. http://dx.doi.org/10.1051/e3sconf/20160711008.

Ferreira O., Viavattene C., Jimenez J.A., Bolle A., Neves Das L., Plomaritis T., McCall R., Van Dongeren A.R., Storm-induced risk assessment: evaluation of two tools at the regional and hotspot scale, Coast. Eng. (2017).

Gallien, T.W., 2016. Validated coastal flood modeling at Imperial Beach, California: comparing total water level, empirical and numerical overtopping methodologies. Coast. Eng. 111, 95–104. http://dx.doi.org/10.1016/j.coastaleng.2016.01.014.

Garrity, N.J., Battalio, R., Hawkes, P.J., Roupe, D., 2007. Evaluation of event and response approaches to estimate the 100-year coastal flood for pacific coast sheltered waters. In: Coast. Eng. 2006. World Scientific Publishing Company, pp. 1651–1663. http://dx.doi.org/10.1142/9789812709554_0140.

Gerl, T., Kreibich, H., Franco, G., Marechal, D., Schröter, K., Schwarz, J., Mifflin, E., Thomas, W., Murphy, J., Jones, C., Lawrence, M., 2016. A review of flood loss models as basis for harmonization and benchmarking. PLoS One 11, e0159791. http://dx.doi.org/10.1371/journal.pone.0159791.

Gopalakrishnan, S., Smith, M.D., Slott, J.M., Brad Murray, A., 2009. The Value of Disappearing Beaches: a Hedonic Pricing Model with Endogenous Beach Width. http://ageconsearch.umn.edu/bitstream/49261/2/AAEA_637249_beach_value_SG_et_al_2009.pdf. (Accessed 9 June 2017).

Gornitz, V.M., 1990. Vulnerability of the east coast. J. Coast. Res. 201–307.

Hajkowicz, S., Higgins, A., 2008. A comparison of multiple criteria analysis techniques for water resource management. Eur. J. Oper. Res. 184, 255–265. http://dx.doi.org/10.1016/j.ejor.2006.10.045.

Hallegatte, S., Green, C., Nicholls, R.J., Corfee-Morlot, J., 2013. Future flood losses in major coastal cities. Nat. Clim. Chang. 3, 802–806. http://dx.doi.org/10.1038/nclimate1979.

Hedges, T.S., Reis, M.T., 1998. Wave overtopping models and seawall freeboards. Water, Marit. Energy J. 1, 1–10. https://www.witpress.com/Secure/elibrary/papers/CE99/CE99052FU.pdf. (Accessed 5 June 2017).

Hinkel, J., Klein, R.J.T., 2009. Integrating knowledge to assess coastal vulnerability to sea-level rise: the development of the DIVA tool. Glob. Environ. Chang. 19, 384–395. http://dx.doi.org/10.1016/j.gloenvcha.2009.03.002.

Holman, R.A., 1986. Extreme value statistics for wave run-up on a natural beach. Coast. Eng. 9, 527–544. http://dx.doi.org/10.1016/0378-3839(8690002-5).

Huang, I.B., Keisler, J., Linkov, I., 2011. Multi-criteria decision analysis in environmental sciences: ten years of applications and trends. Sci. Total Environ. 409, 3578–3594. http://dx.doi.org/10.1016/j.scitotenv.2011.06.022.

IPCC, 2015. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Geneva.
Jiménez, J.A., Ciavola, P., Balouin, Y., Armaroli, C., Bosom, E., Gervais Laboratori, M., Marítima, E., 2009. Geomorphic coastal vulnerability to storms in microtidal fetch-limited environments: application to NW Mediterranean & N Adriatic Seas. J. Coast. Res. J. Coast. Res. SI J. Coast. Res. SI 56, 1641–1645.
Jiménez J.A., Ballesteros C., Sanuy M., Valdemoro H., Storm-induced risks along the coast northwards of Barcelona (NW Mediterranean), Coast. Eng. (2017).
Jongman, B., Kreibich, H., Apel, H., Barredo, J.I., Bates, P.D., Feyen, L., Gericke, A., Neal, J., Aerts, J.C.J.H., Ward, P.J., 2012. Comparative flood damage model assessment: towards a European approach. Nat. Hazards Earth Syst. Sci. 12, 3733–3752. http://dx.doi.org/10.5194/nhess-12-3733-2012.
Karvonen, T., Hepojoki, A., Huhta, H.-K., Louhio, A., 2000. The Use of Physical Models in Dam-break Analysis.
Kriebel, D.L., Dean, R.G., 1993. Convolution method for time-dependant beach-profile response. J. Waterw. Port. Coast. Ocean. Eng. 119.
Larson, M., Kraus, N.C., 1989. SBEACH: Numerical Model for Simulating Storm-induced Beach Change, Vicksburg.
Levy, J.K., 2005. Multiple criteria decision making and decision support systems for flood risk management. Stoch. Environ. Res. Risk Assess. 19, 438–447. http://dx.doi.org/10.1007/s00477-005-0009-2.
Mather, A., Stretch, D., Garland, G., 2011. Predicting extreme wave run-up on natural beaches for coastal planning and management. Coast. Eng. J. 53, 87–109. http://dx.doi.org/10.1142/S0578563411002288.
Matias, A., Blenkinsopp, C.E., Masselink, G., 2014. Detailed investigation of overwash on a gravel barrier. Mar. Geol. 350, 27–38. http://dx.doi.org/10.1016/j.margeo.2014.01.009.
McCall, R.T., Van Thiel de Vries, J.S.M., Plant, N.G., Van Dongeren, A.R., Roelvink, J.A., Thompson, D.M., Reniers, A.J.H.M., 2010. Two-dimensional time dependent hurricane overwash and erosion modeling at Santa Rosa Island. Coast. Eng. 57, 668–683. http://dx.doi.org/10.1016/j.coastaleng.2010.02.006.
McLaughlin, S., McKenna, J., Cooper, J.A.G., 2002. Socio-economic data in coastal vulnerability indices: constraints and opportunities. J. Coast. Res. 487–497.
Mendoza, E.T., Jiménez, J.A., 2006. Storm-induced beach erosion potential on the catalonian coast. In: Coast. Geomorphol. Spain Proc. III Spanish Conf. Coast. Geomorphol, pp. 81–88.
Mendoza, G.A., Martins, H., 2006. Multi-criteria decision analysis in natural resource management: a critical review of methods and new modelling paradigms. For. Ecol. Manag. 230, 1–22. http://dx.doi.org/10.1016/j.foreco.2006.03.023.
Merz, B., Kreibich, H., Schwarze, R., Thieken, A., 2010. Assessment of economic flood damage. Nat. Hazards Earth Syst. Sci. 10, 1697–1724. http://dx.doi.org/10.5194/nhess-10-1697-2010.
Messner, F., Penning-Rowsell, E., Green, C., Meyer, V., Tunstall, S., Van der Veen, A., 2007. Evaluating Flood Damages: Guidance and Recommendations on Principles and Methods.
Meyer, V., Scheuer, S., Haase, D., 2009. A multicriteria approach for flood risk mapping exemplified at the Mulde river, Germany. Nat. Hazards 48, 17–39. http://dx.doi.org/10.1007/s11069-008-9244-4.
Meyer, V., Becker, N., Markantonis, V., Schwarze, R., van den Bergh, J.C.J.M., Bouwer, L.M., Bubeck, P., Ciavola, P., Genovese, E., Green, C., Hallegatte, S., Kreibich, H., Lequeux, Q., Logar, I., Papyrakis, E., Pfurtscheller, C., Poussin, J., Przyluski, V., Thieken, A.H., Viavattene, C., 2013. Review article: assessing the costs of natural hazards – state of the art and knowledge gaps. Nat. Hazards Earth Syst. Sci. 13, 1351–1373. http://dx.doi.org/10.5194/nhess-13-1351-2013.
Narayan, S., Hanson, S., Nicholls, R.J., Clarke, D., Willems, P., Ntegeka, V., Monbaliu, J., 2012. A holistic model for coastal flooding using system diagrams and the Source-Pathway-Receptor (SPR) concept. Nat. Hazards Earth Syst. Sci. 12, 1431–1439. http://dx.doi.org/10.5194/nhess-12-1431-2012.
Narra, P., Coelho, C., Sancho, F., Palalane, J., 2017. CERA: an open-source tool for coastal erosion risk assessment. Ocean. Coast. Manag. 142, 1–14. http://dx.doi.org/10.1016/j.ocecoaman.2017.03.013.
Neumann, B., Vafeidis, A.T., Zimmermann, J., Nicholls, R.J., 2015. Future coastal population growth and exposure to sea-level rise and coastal flooding - a global assessment. PLoS One 10, e0118571. http://dx.doi.org/10.1371/journal.pone.0118571.
Orton, P., Vinogradov, S., Georgas, N., Blumberg, A., Lin, N., Gornitz, V., Little, C., Jacob, K., Horton, R., 2015. New York city panel on climate change 2015 report chapter 4: dynamic coastal flood modeling. Ann. N. Y. Acad. Sci. 1336, 56–66. http://dx.doi.org/10.1111/nyas.12589.
Ouyang, M., Dueñas-Osorio, L., 2014. Multi-dimensional hurricane resilience assessment of electric power systems. Struct. Saf. 48, 15–24. http://dx.doi.org/10.1016/j.strusafe.2014.01.001.
Papaioannou, G., Vasiliades, L., Loukas, A., 2015. Multi-criteria analysis framework for potential flood prone areas mapping. Water Resour. Manag. 29, 399–418. http://dx.doi.org/10.1007/s11269-014-0817-6.
Penning-Rowsell, E., Priest, S., Parker, D., Morris, J., Tunstall, S., Viavattene, C., Chatterton, J., Owen, D., 2013. Flood and Coastal Erosion Risk Management: a Manual for Economic Appraisal.
Plomaritis T.A., Costas S.O., Use of a Bayesian Network for coastal hazards, impact and disaster risk reduction assessment at a coastal barrier (Ria Formosa, Portugal), Coast. Eng. (2017).
Priest, S., Wilson, T., Tapsell, S., Penning-Rowsell, C., Viavattene, E., Fernandez-Bilbao, A., 2007. Building a Model to Estimate Risk to Life for European Flood Events – Final Report.
Przyluski, V., Hallegatte, S., 2011. Indirect Costs of Natural Hazards.
Pullen, T., Allsop, N.W.H., Bruce, T., Kortenhaus, A., Schüttrumpf, H., der Meer, J.W., 2007. EurOtop Wave Overtopping of Sea Defences and Related Structures: Assessment Manual. www.overtopping-manual.com. (Accessed 5 June 2017). http://www.overtopping-manual.com/.
Purvis, M.J., Bates, P.D., Hayes, C.M., 2008. A probabilistic methodology to estimate future coastal flood risk due to sea level rise. Coast. Eng. 55, 1062–1073. http://dx.doi.org/10.1016/j.coastaleng.2008.04.008.
Ramieri, E., Hartley, A., Barbanti, A., Santos, F.D., Gomes, A., Hilden, M., Laihonen, P., Marinova, N., Santini, M., 2011. Methods for Assessing Coastal Vulnerability to Climate Change ETC CCA Technical Paper 1/2011 European Topic Centre on Climate Change Impacts, Vulnerability and Adaptation.
Roberts, T.M., Wang, P., Kraus, N.C., 2010. Limits of wave runup and corresponding beach-profile change from large-scale laboratory data. J. Coast. Res. 261, 184–198. http://dx.doi.org/10.2112/08-1097.1.
Roelvink, D., Reniers, A., van Dongeren, A., van Thiel de Vries, J., McCall, R., Lescinski, J., 2009. Modelling storm impacts on beaches, dunes and barrier islands. Coast. Eng. 56, 1133–1152. http://dx.doi.org/10.1016/j.coastaleng.2009.08.006.
Rose, A., 2010. Economic principles, issues, and research priorities in hazard loss estimation. In: Model. Spat. Econ. Impacts Disasters, pp. 13–36.
Sánchez-Arcilla, A., Jiménez, J.A., Peña, C., 2009. Wave-induced morphodynamic risks. Characterization of extremes. In: Proc. Coast. Dyn. 2009 Impacts Hum. Act. Dyn. Coast. Process., Tokyo.
Satta, A., Snoussi, M., Puddu, M., Flayou, L., Hout, R., 2016. An Index-based Method to Assess Risks of Climate-related Hazards in Coastal Zones: the Case of Tetouan. http://dx.doi.org/10.1016/j.ecss.2016.03.021.
Schanze, J., Zeman, E., Marsalek, J., 2006. Flood Risk Management: Hazards, Vulnerability and Mitigation Measures. Springer.
Serre D., Advanced methodology for risk and vulnerability assessment of interdependency of critical infrastructure in respect to urban floods, (n.d.). https://www.e3s-conferences.org/articles/e3sconf/pdf/2016/02/e3sconf_flood2016_07002.pdf (accessed June 16, 2017).
Smallegan, S.M., Irish, J.L., Van Dongeren, A.R., Den Bieman, J.P., 2016. Morphological response of a sandy barrier island with a buried seawall during Hurricane Sandy. Coast. Eng. 110, 102–110. http://dx.doi.org/10.1016/j.coastaleng.2016.01.005.
Splinter, K.D., Carley, J.T., Golshani, A., Tomlinson, R., 2014. A Relationship to Describe the Cumulative Impact of Storm Clusters on Beach Erosion. http://dx.doi.org/10.1016/j.coastaleng.2013.10.001.
Stockdon, H.F., Holman, R.A., Howd, P.A., Sallenger, A.H., 2006. Empirical parameterization of setup, swash, and runup. Coast. Eng. 53, 573–588. http://dx.doi.org/10.1016/j.coastaleng.2005.12.005.
Tanenbaum, A.S., 1981. Connectivity analysis. Comput. Netw. 36–56.
Tapsell, S.M., Penning-Rowsell, E.C., Tunstall, S.M., Wilson, T.L., 2002. Vulnerability to flooding : health and social dimensions. Philos. Trans. R. Soc. Lond. A Math. Phys. Eng. Sci. 360, 1511–1525. http://dx.doi.org/10.1098/rsta.2002.1013.
Tapsell S.M., Priest S.J., Wilson T., Viavattene C., Penning-Rowsell E.C., A new model to estimate risk to life for European flood events, in: FLOODrisk Eur. Conf. Flood Risk Manag. into Pract., Oxford, n.d.
Thieler, E.S., Hammer-Close, E.R., 1999. National Assessment of Coastal Vulnerability to Sea-level Rise.
Torresan, S., Critto, A., Rizzi, J., Marcomini, A., 2012. Assessment of coastal vulnerability to climate change hazards at the regional scale: the case study of the North Adriatic Sea. Nat. Hazards Earth Syst. Sci. 12, 2347–2368. http://dx.doi.org/10.5194/nhess-12-2347-2012.
Torresan, S., Critto, A., Rizzi, J., Zabeo, A., Furlan, E., Marcomini, A., 2016. DESYCO: a decision support system for the regional risk assessment of climate change impacts in coastal zones. Ocean. Coast. Manag. 120, 49–63. http://dx.doi.org/10.1016/j.ocecoaman.2015.11.003.
Torresan, S., Critto, A., Rizzi, J., Zabeo, A., Furlan, E., Marcomini, A., 2016. DESYCO: a decision support system for the regional risk assessment of climate change impacts in coastal zones. Ocean. Coast. Manag. 120, 49–63. http://dx.doi.org/10.1016/j.ocecoaman.2015.11.003.
UNISDR, 2015. Disaster Risk Reduction and Resilience in the 2030 Agenda for Sustainable Development.
Vafeidis, A.T., Nicholls, R.J., McFadden, L., Tol, R.S.J., Hinkel, J., Spencer, T., Grashoff, P.S., Boot, G., Klein, R.J.T., 2008. A new global coastal database for impact and vulnerability analysis to sea-level rise. J. Coast. Res. 244, 917–924. http://dx.doi.org/10.2112/06-0725.1.
De Vet, P., Lodewijk, M., McCall, R.T., Den Bieman, J.P., StiveE, M.J.F., Van Ormondt, M., 2015. Modelling dune erosion, overwash and breaching at fire island (NY) during Hurricane Sandy. In: Proc. Coast. Sediments 2015, WORLD SCIENTIFIC. http://dx.doi.org/10.1142/9789814689977_0006.
Viavattene, C., Priest, S., Parker, D., Owen, D., 2014. From Theory to Practice: can we really value coastal flood impacts?. In: Proc. Int. Conf. Flood Manag., Sao Paulo.
Viavattene, C., Jimenez, J.A., Owen, D., Priest, S.J., Parker, D.J., Micou, P., Ly, S., 2015. Coastal Risk Assessment Framework: Guidance Document.
Viavattene, C., Micou, A.P., Owen, D.J., Priest, S., Parker, D.J., 2015. Library of Coastal Vulnerability Indicators.
Viavattene, C., Priest, S.J., Owen, D., Parker, D.J., Micou, P., Ly, S., 2016. INDRA model: for a better assessment of coastal events disruptions. In: ISCRAM 2016 Conf. Proc. – 13th Int. Conf. Inf. Syst. Cris. Response Manag.
Vousdoukas, M.I., Wziatek, D., Almeida, L.P., 2012. Coastal vulnerability assessment based on video wave run-up observations at a mesotidal, steep-sloped beach. Ocean. Dyn. 62, 123–137. http://dx.doi.org/10.1007/s10236-011-0480-x.
Vousdoukas, M.I., Voukouvalas, E., Mentaschi, L., Dottori, F., Giardino, A., Bouziotas, D., Bianchi, A., Salamon, P., Feyen, L., 2016. Developments in large-scale coastal flood

hazard mapping. Nat. Hazards Earth Syst. Sci. 16, 1841–1853. http://dx.doi.org/10.5194/nhess-16-1841-2016.
Wise, R.S., Smith, S.J., Larson, M., 1996. SBEACH. Numerical Model for Simulating Storm-induced Beach Change, Vicksburg.
Zanuttigh, B., Simcic, D., Bagli, S., Bozzeda, F., Pietrantoni, L., Zagonari, F., Hoggart, S., Nicholls, R.J., 2014. THESEUS decision support system for coastal risk management. Coast. Eng 87, 218–239. http://dx.doi.org/10.1016/j.coastaleng.2013.11.013.